Detection of Congestive Heart Failure Using Time-Domain Methods And Poincaré Plot of Heart Rate Variability Signals

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Abstract—**Congestive heart failure [CHF] is a common and serious medical condition where the heart is not able to pump enough blood to meet the body's energy demands. Heart failure typically develops slowly after injury to the heart, such as a heart attack, too much strain on the heart due to years of untreated high blood pressure or a diseased heart valve. In this study, we consider the problem of detection of congestive heart failure using heart rate variability analysis techniques, which depends on the variations between consecutive heartbeats. The problem is divided into feature extraction and classification stages. Heart rate variability analysis methods such as time-domain analysis and nonlinear method (Poincaré Plot) are used to extract the features. For classification, voting k-nearest neighbor classifier and back propagation neural networks are used. Results have shown that these classifiers are capable of detecting congestive heart failure especially after normalizing the features used in classification. Time-domain features are capable of representing the normal and CHF signals more than Poincaré plot features.**

Keywords— **HRV, CHF, Time-domain Analysis, Poincaré Plot, Back propagation Neural Networks**

I. INTRODUCTION

More than 20 million people around the world (nearly 5 million in the United States) have heart failure. Heart failure is the first cause of hospitalization for people aged 65 and older. About 550,000 people in United States only develop Congestive Heart Failure each year with annual mortality of 266,000, and the number of people living with heart failure is growing [1, 2, 3]. Early diagnosis of heart failure is required specially that it is not always apparent. But if not diagnosed, it may be severe and patient will be more liable to sudden cardiac death. ECG records cannot diagnose heart failure; it is only an indicator of heart problems, so physicians need other tests to diagnose heart failure.

Heart Rate Variability (HRV) signal, representing heart rate and beat to beat variations, is another signal that can be extracted from ECG signal. HRV can be used for automatic detection of heart failure through some analysis techniques. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem.

HRV has been the subject of numerous clinical studies investigating a wide spectrum of cardiac and non-cardiac diseases and clinical conditions, such as: myocardial infarction (MI) [4, 5, 6, 7], sudden cardiac death and ventricular arrhythmias [8, 9, 10, 11], Hypertension [12, 13], Diabetes mellitus [14, 15, 16], and Heart transplantation [17, 18, 19, 20]. Many studies analyzed the HRV during CHF. In 1989, Casolo [21] has used time-domain RR interval histogram with 24-hour Holter to compare CHF patients group with control group. In 1994, Woo [22] used the Poincaré plot method to assist the analysis of sympathetic influences. In 1999, Bonaduce et al [23] designed a study to evaluate the predictive value of HRV and Poincaré plots as assessed by 24-hour holter recording in patients with chronic heart failure.

In this study, two of the HRV analysis techniques are considered, time-domain methods which can be statistical or geometrical, and a nonlinear method called Poincaré plot. The detection problem is divided into two stages: feature extraction and classification.

II. FEATURE EXTRACTION

This section describes the used feature extraction techniques.

A. Time-Domain Methods

Parameters in the time domain are the simplest ones to calculate. To get these parameters either statistical or geometrical methods are used.

Using statistical methods, the simplest variables to calculate are the mean and the standard deviation of the RR interval (or NN "Normal-to-Normal" as only sinus beats have to be analyzed [24]) [SDNN]. SDNN reflects all the cyclic components responsible for variability in the period of recording. Other measures can be derived from interval differences such as RMSSD, the root mean square of differences of successive NN intervals., NN50, the number of interval differences of successive NN intervals greater than 50 ms, and pNN50 the proportion derived by dividing NN50 by the total number of NN intervals. All these measurements of short-term variation estimate high frequency variations in heart rate and thus are highly correlated [25]. Instantaneous heart rate (IHR) is another descriptive signal that reflects the change in the heart rate instantaneously and it can be calculated from the NN interval tachogram. It is equal to 1 / NN interval.

In the present work, short-term HRV signals (2-5 min) will be used.

The series of NN intervals can also be converted into a geometric pattern, such as the sample density distribution of NN interval durations. Most geometric methods require the RR (or NN) interval sequence to be measured on or converted to a discrete scale which is not too fine or too coarse and which permits the construction of smoothed histograms. Most experience has been obtained with bins approximately 8 ms long (precisely 7.8125 ms= 1/128 s)

which corresponds to the precision of current commercial equipment. Two measures are selected: "HRV triangular index" which is the integral of the density distribution (i.e. the number of all NN intervals) divided by the maximum of the density distribution. Using a measurement of NN intervals on a discrete scale, the measure is approximated by the value: (total number of NN intervals)/ (number of NN intervals in the modal bin) which is dependent on the length of the bin, i.e. on the precision of the discrete scale of measurement. The other is the "triangular interpolation of NN interval histogram (TINN)" which is the baseline width of the minimum square difference triangular interpolation of the highest peak of the histogram of all NN intervals.

B. Poincaré Plot

Non-linear phenomena are certainly involved in the genesis of HRV. They are determined by complex interactions of hemodynamic, electrophysiological and humoral variables, as well as by autonomic and central nervous regulations. It has been speculated that analysis of HRV based on the methods of non-linear dynamics might elicit valuable information for the physiological interpretation of HRV and for the assessment of the risk of sudden death.

One simple and easy to comprehend nonlinear method, which is used here, is the so called "Poincaré plot". It is a graphical presentation of the correlation between consecutive RR intervals. It is a graph of each RR interval plotted against the next interval. Poincarè plot analysis is an emerging quantitative-visual technique whereby the shape of the plot is categorized into functional classes that indicate the degree of heart failure in a subject. The plot provides summary information as well as detailed beat-to-beat information on the behavior of the heart [26].

Poincarè plot are most often taken of 5-10 minutes intervals, like in this work, or of a 24-h segment. For 5-10 minutes segments, wide-sense stationarity may be assumed. The RR interval Poincarè plot typically appears as an elongated cloud of points oriented along the line-of-identity at 45° to the normal axis, see Fig. 1. The dispersion of points perpendicular to the line-of-identity reflects the level of short-term variability. The dispersion of points along the line-of-identity is thought to indicate the level of long-term variability [27]. To characterize the shape of the plot mathematically, most researches have adopted the technique of fitting an ellipse to the plot, as in Fig. 1. A set of the axis oriented with the line-of-identity is defined. The axes of the Poincarè plot are related to the new set of axis by a rotation of $\theta = \pi / 4$ rad.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \cos\ \theta & -\sin\ \theta \\ \sin\ \theta & \cos\ \theta \end{bmatrix} \begin{bmatrix} RR_n \\ RR_{n+1} \end{bmatrix} \quad (1)$$

In the reference system of the new axis, the dispersion of the points around the x_1 axis is measured by the standard deviation denoted by SD1. This quantity measures the width of the Poincarè cloud and, therefore, indicates the level of short-term HRV. The length of the cloud along the line-of-identity measures the long-term HRV and is measured by SD2 which is the standard deviation around the x_2 [26].

C. Normalization

A large set of parameters would be obtained, and every one has a different range of values according to its type. The effect of normalization of all parameter values in the features vector within a fixed range around the zero (e.g., between ± 1) is studied as a possible convenient preprocessing step for proper weighting of parameters used in the classification [28, 29]. The normalized parameter is calculated using equation (2).

$$Normalized\,Parameter = \frac{2*(OriginalParameter - \min)}{(\max - \min)} - 1 \quad (2)$$

III. CLASSIFICATION

In order to investigate the performance of the proposed features in detecting the CHF, we attempt to implement some of the most commonly used classifiers and use them to perform this task. Voting k-nearest neighor classifier and backpropagation neural network classifier are used.

The performance of the algorithms is reported in terms of sensitivity, specificity, positive predictive accuracy, and error rate. These values are standard statistics used to measure the performance of the classification algorithms [30]. Sensitivity measures how well the algorithm can identify CHF signals, specificity measures how well the algorithm identifies the signal NOT in CHF, positive predictive accuracy measures how often the algorithm is correct when it calls a signal CHF, and error rate is a single value summary of the overall percentage of mistakes made by the algorithm.

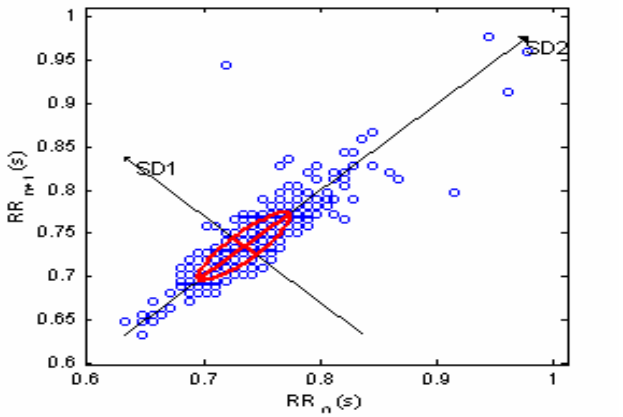

Fig. 1. Poincarè Plot.

A) Voting k-Nearest Neighbor (k-NN) Classifier

It is a non-parametric statistical classifier. It assigns a test sample to the class of the majority of its k-neighbors [28]. That is, assuming the number of voting neighbors to be $k = \sum_{i=1}^{2} k_i$ (where k_i is the number of samples from class i in the k-sample neighborhood of the test sample), the test sample is assigned to class m if $k_m = \max\{k_i, i=1,2\}$.

B) Back propagation Neural Networks

In the present work, "Resilient Back propagation" training algorithm was used. Multilayer networks typically use sigmoid transfer functions in the hidden layers. Here, this network is used with 2 neurons in hidden layer, 2 neurons in the output layer, and number of neurons in the input layer is variable according to the features vector length. The network is trained to output equals (1) in the correct position of the output vector and to fill the rest of the output vector with 0's, if the input is the features of normal signal then the output will be (1) in the first neuron and (0) in the second and vise versa.

IV. RESULTS

A. Data Collection

The HRV signals used in this work were obtained from PhysioBank [31]. The normal signals were obtained from "Normal Sinus Rhythm RR Interval Database" and "The MIT-BIH Normal Sinus Rhythm Database", while CHF signals were obtained from "Congestive Heart Failure RR Interval Database" and "The BIDMC Congestive Heart Failure Database". HRV signals were driven from ECG signals using annotation files.

Since in the present work, short-term HRV signals (2-5 minutes) were used, the extraction of short-term HRV signals from the overall of 106 long-term signals (from all databases) is needed. So the data set used consists of 600 short-term HRV signals divided to: 400 for design (learning) subset as 200 for normal signals and 200 for CHF signals, and 200 for test subset as 100 for normal signals and 100 for CHF signals.

Learning and testing subsets are fixed for different classifiers to neutralize their effect on results [28].

B. Classification Results

The specificity (spec.), sensitivity (sens.), positive predictive accuracy (+ve pred.) and error rate (err.) results of applying the voting k-NN classifier and backpropagation neural networks on the feature vectors before and after normalization are shown in tables 1 to 6.

V. DISCUSSION

It is obvious also from classification results that normalizing the feature vectors has been shown to improve the overall accuracy, indicating its importance as a preprocessing step.

Voting k-nearest neighbor classifier and back propagation neural networks have shown a high level of accuracy in case of time-domain feature vector. It can be explained by the inherited independence of these techniques from the data distribution by being sample-based. While classification using Poincarè plot features hasn't shown good results. Brennan [26] has shown that these features, i.e. SD1 and SD2, are related to linear indices of HRV, specifically the SDNN (the standard deviation of the RR interval) and SDSD (the standard deviation of the successive differences). Since SDNN as a statistical feature does not show a significant difference between normal and CHF signals, so this is the case for the Poincarè plot features in turn.

VI. CONCLUSION

Two methods for detecting CHF using HRV analysis are presented. Two stages are required in order to detect CHF, feature extraction and classification. In the feature extraction stage, the features are extracted using time-domain methods, and nonlinear method (Poincaré Plot). These features are normalized before entered to classification stage. The classification takes place using Voting k-Nearest Neighbor Classifier, and Backpropagation Neural Networks.

Results have shown that a good promise for an automatic detection of CHF signals using voting k-nearest neighbor classifier and backpropagation neural networks.

It is concluded that time-domain features are capable of representing the normal and CHF signals more than the Poincaré plot feature. In addition, normalization of the feature vectors before classification has a great effect in improving the detection accuracy.

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TABLE 1
VOTING K-NN CLASSIFIER – TIME-DOMAIN FEATURES

k	Before Normalization				After Normalization			
	Sens.	Spec.	+ve Pred.	Err.	Sens.	Spec.	+ve Pred.	Err.
1	65.80%	67.20%	66.27%	33.50%	92.80%	95.70%	93.00%	5.75%
2	84.00%	83.30%	83.89%	16.35%	97.40%	98.90%	97.44%	1.85%
3	68.00%	65.70%	67.25%	33.15%	94.50%	94.00%	94.47%	5.75%
4	80.00%	77.90%	79.57%	21.05%	96.70%	96.60%	96.70%	3.35%
5	68.80%	66.10%	67.93%	32.55%	94.40%	93.40%	94.34%	6.10%
6	76.80%	77.70%	77.01%	22.75%	96.50%	96.30%	96.49%	3.60%
7	68.30%	65.70%	67.45%	33.00%	93.90%	93.00%	93.84%	6.55%
8	76.80%	73.60%	76.03%	24.80%	95.00%	94.90%	94.99%	5.05%
9	70.00%	64.80%	68.35%	32.60%	93.20%	92.20%	93.13%	7.30%

TABLE 2
VOTING K-NN CLASSIFIER INCONCLUSIVE RATES – TIME-DOMAIN FEATURES

k	Before Normalization		After Normalization	
	Normal	CHF	Normal	CHF
1	0.00%	0.00%	0.00%	0.00%
2	38.30%	37.10%	11.60%	10.70%
3	0.00%	0.00%	0.00%	0.00%
4	24.60%	26.10%	6.00%	7.00%
5	0.00%	0.00%	0.00%	0.00%
6	17.90%	24.20%	5.10%	7.50%
7	0.00%	0.00%	0.00%	0.00%
8	16.60%	19.50%	3.60%	5.00%
9	0.00%	0.00%	0.00%	0.00%

TABLE 3
VOTING K-NN CLASSIFIER – POINCARE PLOT FEATURES

k	Before Normalization				After Normalization			
	Sens.	Spec.	+ve Pred.	Err.	Sens.	Spec.	+ve Pred.	Err.
1	69.10%	66.80%	68.37%	32.05%	70.40%	66.90%	69.33%	31.35%
2	85.60%	79.60%	84.68%	17.40%	85.50%	81.90%	84.96%	16.30%
3	73.90%	65.40%	71.48%	30.35%	72.80%	69.80%	71.96%	28.70%
4	82.80%	77.40%	81.82%	19.90%	81.90%	79.40%	81.44%	19.35%
5	75.10%	70.00%	73.76%	27.45%	73.20%	70.40%	72.43%	28.20%
6	82.10%	76.40%	81.02%	20.75%	80.40%	78.80%	80.08%	20.40%
7	76.10%	71.10%	74.84%	26.40%	73.90%	72.50%	73.53%	26.80%
8	81.20%	76.00%	80.17%	21.40%	79.50%	77.00%	78.97%	21.75%
9	77.70%	70.50%	75.97%	25.90%	73.60%	72.10%	73.20%	27.15%

TABLE 4
VOTING K-NN CLASSIFIER INCONCLUSIVE RATES – POINCARE PLOT FEATURES

k	Before Normalization		After Normalization	
	Normal	CHF	Normal	CHF
1	0.00%	0.00%	0.00%	0.00%
2	33.20%	28.50%	34.60%	30.10%
3	0.00%	0.00%	0.00%	0.00%
4	18.40%	21.70%	21.70%	19.20%
5	0.00%	0.00%	0.00%	0.00%
6	13.90%	14.20%	15.40%	14.50%
7	0.00%	0.00%	0.00%	0.00%
8	9.80%	11.30%	12.10%	9.90%
9	0.00%	0.00%	0.00%	0.00%

TABLE 5
BACKPROPAGATION NEURAL NETWORKS – TIME-DOMAIN FEATURES

	Before Normalization	After Normalization
Sensitivity	67.00%	97.90%
Specificity	67.00%	98.20%
Positive Predictive Accuracy	69.43%	98.19%
Error Rate	31.25%	01.95%

TABLE 6
BACKPROPAGATION NEURAL NETWORKS – POINCARE PLOT FEATURES

	Before Normalization	After Normalization
Sensitivity	66.30%	71.70%
Specificity	75.90%	68.90%
Positive Predictive Accuracy	73.34%	69.74%
Error Rate	28.90%	29.70%

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